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1 **Current and future perspectives for wastewater-based epidemiology as a**
2 **monitoring tool for pharmaceutical use**

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20
21 **Key words**

- 22 • Wastewater-based epidemiology
- 23 • Drug Utilization Research
- 24 • Pharmacoepidemiology
- 25 • Pharmaceutical (mis)use

26

27 **Abstract**

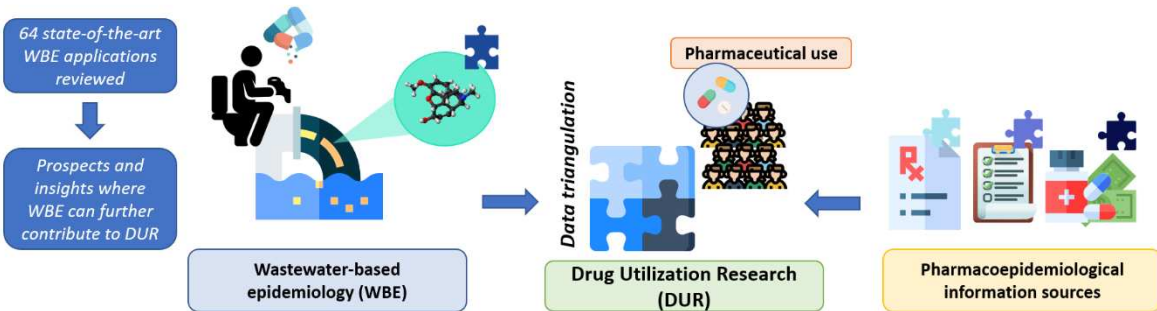
28 The medical and societal consequences of the misuse of pharmaceuticals clearly justifies the need for
29 comprehensive drug utilization research (DUR). Wastewater-based epidemiology (WBE) employs the analysis of
30 human metabolic excretion products in wastewater to monitor consumption patterns of xenobiotics at the
31 population level. Recently, WBE has demonstrated its potential to evaluate lifestyle factors such as illicit drug,
32 alcohol and tobacco consumption at the population level, in near real-time and with high spatial and temporal
33 resolution. Up until now there have been fewer WBE studies investigating health biomarkers such as
34 pharmaceuticals.

35 WBE publications monitoring the consumption of pharmaceuticals were systematically reviewed from three
36 databases (PubMed, Web of Science and Google Scholar). 64 publications that reported population-normalised
37 loads or defined daily doses of pharmaceuticals were selected.

38 We document that WBE could be employed as a complementary information source for DUR. Interest in using
39 WBE approaches for monitoring pharmaceutical use is growing but more foundation research (e.g. compound-
40 specific uncertainties) is required to link WBE data to routine pharmacoepidemiologic information sources and
41 workflows. WBE offers the possibility of i) estimating consumption of pharmaceuticals through the analysis of
42 human metabolic excretion products in wastewater; ii) monitoring spatial and temporal consumption patterns of
43 pharmaceuticals continuously and in near real-time; and iii) triangulating data with other DUR information sources
44 to assess the impacts of strategies or interventions to reduce inappropriate use of pharmaceuticals.

45 **Graphical abstract**

How can WBE be employed as a complementary information source in DUR?

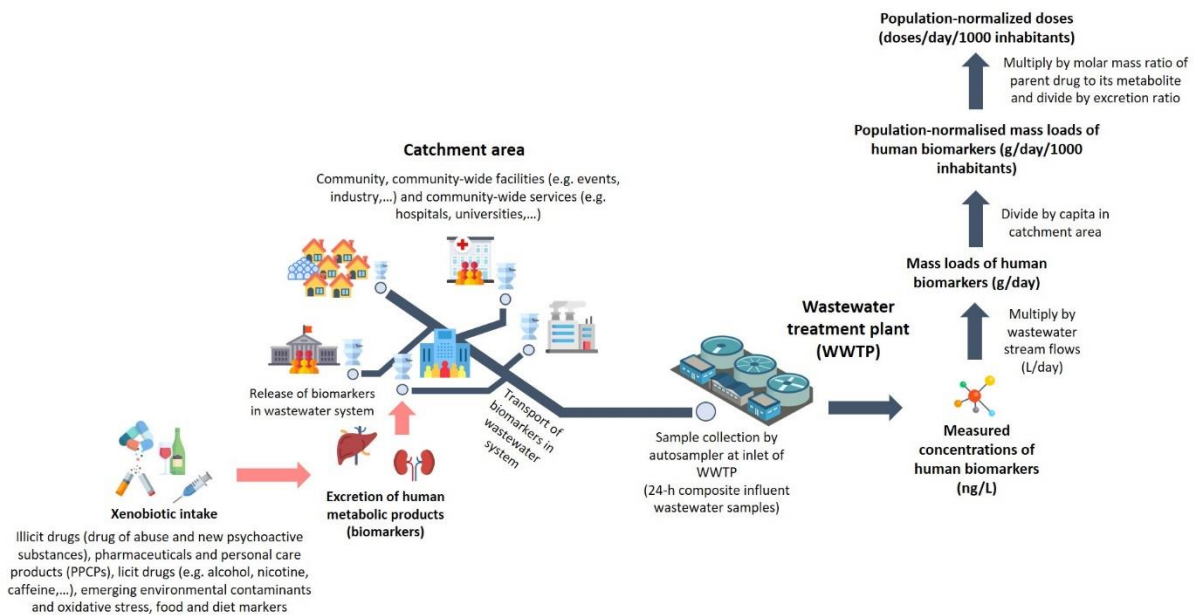


47 **1. Introduction**

48 The development of new and more effective pharmaceuticals in the last decades has contributed to a significant
49 decrease in mortality, an improved quality of life for people with chronic illnesses and reduced time in hospital
50 (Lichtenberg, 2014; Poluzzi et al., 2016). Nevertheless, misuse and abuse of pharmaceuticals can also have
51 negative consequences, such as increased emergency room visits, treatment admissions for prescription drug use
52 disorders and overdose deaths (National Institute of Drug Abuse, 2018; Poluzzi et al., 2016). In addition, 20% of
53 health spending is wasteful and can be reduced by preventing the misuse and mis- and overprescription of
54 pharmaceuticals (Organisation for Economic Co-operation and Development, 2018). The medical consequences
55 and economic burden of the inappropriate use of pharmaceuticals has encouraged comprehensive drug utilization
56 research (DUR) over the past decades (Poluzzi et al., 2016). Currently, DUR relies on data from the sales, billing,
57 prescription and movement through the distribution chain of pharmaceuticals. All of this information is necessary
58 to ensure the availability of safe, high-quality and efficacious treatments (World Health Organization, 2003). These
59 information sources can be used to establish utilization patterns for specific pharmaceuticals and may provide a
60 proxy for the prevalence of the diseases treated by these drugs (Chen & Briesacher, 2011; World Health
61 Organization, 2003). Definitions for DUR terminology can be found in Table S1.

62 Data on the illegal trade or clandestine manufacturing of pharmaceuticals are not covered by traditional DUR
63 figures (Diamanti et al., 2019; European Monitoring Centre for Drugs and Drug Addiction, 2019b), which can
64 lead to an underestimation of pharmaceutical consumption (van Nuijs et al., 2015). In some health care systems,
65 incomplete coverage of these data sources might lead to gaps between the number of prescriptions and overall
66 drug utilisation (i.e. scripts may not be filled, filled scripts may not be consumed, and pharmaceuticals may not be
67 taken in the recommended doses or by the person for whom they were prescribed). Additionally, the locality where
68 a prescription is filled may differ from where consumption occurs. Some patients may not be able to afford to fill
69 their prescriptions, particularly when it comes to repeat prescriptions or due to associated costs or unwanted side
70 effects. These data also do not always include information on the amounts of pharmaceuticals used in hospitals
71 and so may only record the use of reimbursed pharmaceuticals. (Poluzzi et al., 2016; World Health Organization,
72 2003). Furthermore, a limitation of currently used methods for drug utilisation data is the lack of spatial specificity,
73 the lag in data acquisition and the infrequency of data reporting (e.g. this is often only be done on a yearly basis).
74 The resolution of the data is also dependent on the quality of the health care system and may differ between
75 jurisdictions within the same country.

76 In order to provide community-health information on exposure to xenobiotics, wastewater-based epidemiology
77 (WBE) measures biomarker concentrations in untreated wastewater and converts these to per capita mass load
78 estimates using daily wastewater flow rates and population number in the catchment area (Fig. 1) (Boogaerts,
79 Covaci, Kinyua, Neels, & van Nuijs, 2016; P. Choi et al., 2018; Daughton, 2018; Lai et al., 2013; van Wel et al.,
80 2016; Zuccato, Chiabrando, Castiglioni, Bagnati, & Fanelli, 2008). Target analytes can be quantified at trace levels
81 (ng/L) by applying specific, accurate and precise bioanalytical methods such as solid phase extraction and liquid
82 chromatography mass spectrometry (LC-MS/MS) (Andrés-Costa, Andreu, & Picó, 2017; Baker & Kasprzyk-
83 Hordern, 2011a; Botero-Coy et al., 2018; Fatta, Achilleos, Nikolaou, & Meriç, 2007). Although WBE is a
84 relatively new scientific discipline, it has rapidly realised its potential to provide independent, timely, low
85 cost/resource and complementary epidemiologic information on the exposure to and consumption of xenobiotics
86 at high spatial and temporal resolutions (Banta-Green et al., 2009; Huerta-Fontela, Galceran, Martin-Alonso, &
87 Ventura, 2008; Karolak, Nefau, Bailly, Solgadi, & Levi, 2010; Kasprzyk-Hordern, Dinsdale, & Guwy, 2009; Mari
88 et al., 2009; Metcalfe, Tindale, Li, Rodayan, & Yargeau, 2010; Postigo, López de Alda, & Barceló, 2010; Terzic,
89 Senta, & Ahel, 2010; van Nuijs et al., 2009; Zuccato et al., 2005). This is reflected in the increasing numbers of
90 publications in this field (Fig. S1) (P. Choi et al., 2018). The majority of WBE research has focussed on back-
91 estimating illicit drug consumption and only a few have investigated the use of pharmaceuticals (P. Choi et al.,
92 2018; Gracia-Lor et al., 2017). In addition, most of the WBE applications on pharmaceuticals i) have used these
93 data to estimate population size (P. Choi et al., 2018; Lai et al., 2011); ii) to evaluate the illegal use of specific
94 pharmaceuticals (P. Choi et al., 2018; Thai, Lai, Edirisinghe, et al., 2016) or iii) to associate pharmaceutical loads
95 with environmental stressors (P. Choi et al., 2018; Phung et al., 2017).



96

97 **Fig. 1 Schematic overview of WBE for determining pharmaceutical consumption.** Adapted from Choi et al (P. Choi et al.,
98 2018).

99 Importantly, WBE cannot provide any information on the characteristics of the user and his personal
100 consumption. That is, it cannot tell us about: the administration form, co-consumption, dose purity, dose frequency,
101 individual compliance, drug use preferences, or the socio-demographic characteristics of individual patients. Nor
102 can diversion and changes within the drug-using cohort be quantified by WBE. Specifically, if an increase was
103 observed WBE cannot distinguish between the following possibilities i) more individuals are consuming at the
104 same rate, ii) slightly more individuals consuming and at a higher rate each, iii) the same number of individuals
105 consuming a higher total amount each, or iv) one group of individuals in the cohort consuming more than another
106 group. Nevertheless, wastewater samples can be analyzed retrospectively to provide aggregated consumption
107 estimates (Boogaerts et al., 2016; Burgard et al., 2019; Mackie et al., 2019) with easily adjusted spatio-temporal
108 frequencies and short time-lags in gathering and reporting data. While specific socio-demographic features of
109 individuals might not easily be obtained, WBE can provide a spatial comparison between different populations
110 with different socio-economic status at a community level (P. Choi et al., 2019).

111 We review the current situation of applying WBE towards understanding pharmaceutical consumption and provide
112 an overview of analytical information and biomarkers used to monitor pharmaceutical use in defined population
113 groups. Our aim is to document state-of-the art WBE applications on pharmaceutical consumption to give a better
114 understanding on the future research that is needed to move forward WBE as a complementary epidemiological

115 information source in DUR. In this lights, this review aims to provide key insights and prospects where WBE can
 116 further contribute to DUR.

117 2. Literature search and eligibility criteria

118 Multiple literature searches were conducted (between July 2020 and March 2021) to identify all publications (i.e.
 119 research papers, short reports, letters,...) on WBE investigations of pharmaceutical consumption. PubMed, Web
 120 of Science and Google Scholar were queried as illustrated in Table 1. Since WBE was first applied in 2008, we
 121 only searched for publications between 2008 and March 2021. An updated search was performed on a monthly
 122 basis to identify new emerging WBE applications on pharmaceuticals.

123 *Table 1 Applied search combinations during the advanced literature search*

Specified search terms	Search records
(sewage OR wastewater OR "wastewater epidemiology") AND (pharmaceuticals OR medicines)	6498
((wastewater OR sewage OR "wastewater based epidemiology") AND ("pharmaceuticals" OR "medicines")) AND consum*	350
(((((wastewater) OR sewage) AND influent) AND pharmaceuticals) NOT "removal efficien*") NOT sludge	165
((("wastewater epidemiology") OR "sewage epidemiology") OR "wastewater based epidemiology") AND pharmaceuticals) AND consum*	71
(sewage OR wastewater OR "wastewater epidemiology") AND pharmaceutical AND "influent wastewater"	45
((("wastewater based epidemiology") AND (pharmaceutical OR medicines)) AND (consumption OR "population normalised"))	28
("wastewater epidemiology"[Title/Abstract] OR sewage [Title/Abstract] OR wastewater[Title/Abstract]) AND (pharmaceuticals OR medicines) AND "population health"	26
wastewater AND influent AND pharmaceutical AND loads NOT effluent	16

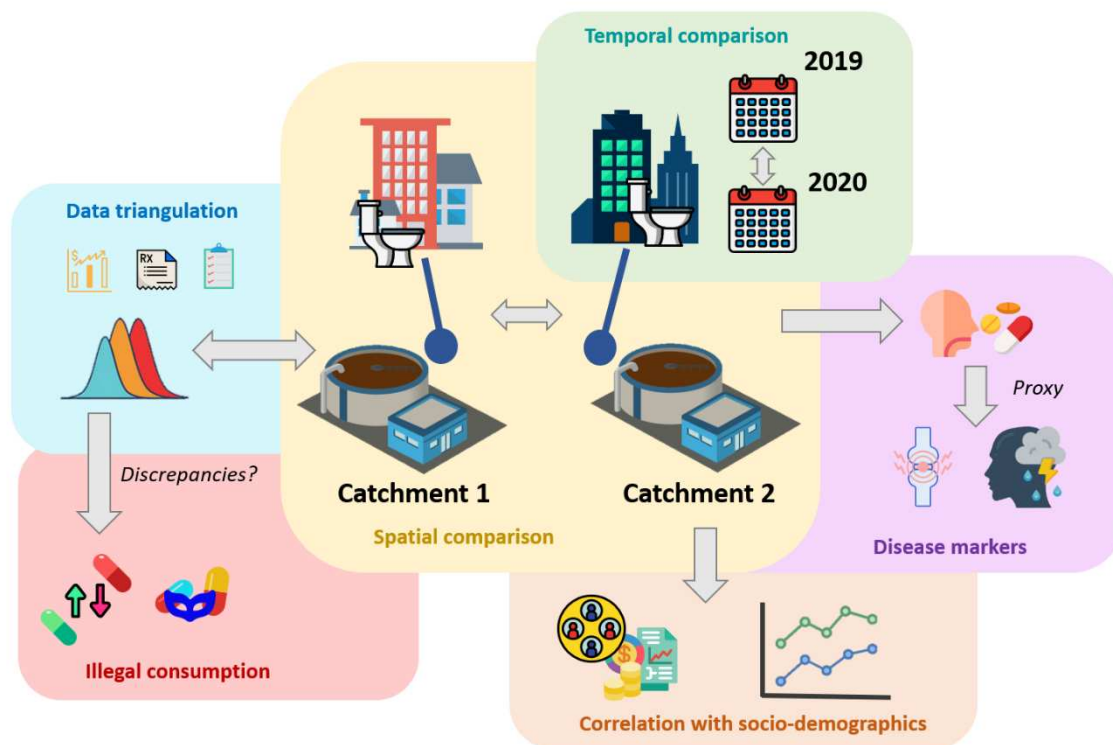
124
 125 Table 1 describes the different keyword combinations that were applied to identify eligible studies for this review.
 126 After a preliminary screening against the eligibility criteria, 122 publications were selected from this wide range
 127 of search records. This initial search was further screened against the strict inclusion criteria defined below. This
 128 final screening resulted in 64 publications qualified for full text review. While the total number of WBE
 129 applications on pharmaceuticals is relatively small, interest in this field of research has grown for the last six years
 130 (~ 9 papers per year on average), as illustrated in Fig S1. Numerous other studies report concentrations of
 131 pharmaceuticals in influent wastewater (IWW) (Baker & Kasprzyk-Hordern, 2011b; Bodik, Mackulak, Faberova,
 132 & Ivanova, 2016). However, in WBE, concentrations are not suitable to estimate community-wide use of
 133 pharmaceuticals because of fluctuations in flow rates and population sizes. For this reason, it is imperative to
 134 normalize measured concentrations for varying population sizes and flow rates to allow reliable comparisons
 135 between locations. Additionally, these descriptive studies did not triangulate with other data of tested specific

136 hypothesis about the spatio-temporal patterns of use. Therefore, these studies were not included in this review. By
137 normalizing to population sizes and flow rates, WBE offers the possibility to compare intra- and intercountry
138 normalized-loads of pharmaceuticals (Ahmed et al., 2020; Bodik et al., 2016; Pereira, Silva, Meisel, Lino, & Pena,
139 2015). For these reasons, the selection of eligible cases goes beyond simply reporting of pharmaceutical
140 concentrations in IWW.

141 We included (i) WBE studies that estimated population-normalised mass loads of excreted human metabolic
142 pharmaceutical biomarkers (mg/day/1000 inhabitants) and (ii) WBE studies in which pharmaceutical doses were
143 back-calculated using measured concentrations of the biomarkers (doses/day/inhabitant). For this purpose, we
144 excluded wastewater studies on pharmaceuticals that focused exclusively on (i) method development and
145 validation; (ii) evaluating removal efficiencies during wastewater treatment; (iii) investigating pharmaceuticals as
146 a potential source of contamination in aquatic environments and (iv) evaluating the use pharmaceutical
147 concentrations as population size markers. Citation tracking and searches in author's bibliographies were
148 performed to track down additional references. Detailed information on the applied analytical techniques and
149 current WBE biomarkers is given elsewhere (Baker & Kasprzyk-Hordern, 2011a; P. Choi et al., 2018; Gracia-Lor
150 et al., 2017; van Nuijs et al., 2011).

151 **3. WBE applications on pharmaceuticals: state-of-the-art applications**

152 The final selection of 64 WBE applications can be categorized in different types including spatial and temporal
153 comparisons, triangulating with sales and/or prescription statistics, monitoring pharmaceuticals as proxies of
154 disease, correlations with socio-demographics, and evaluating illicit use of pharmaceuticals (Fig. 2). Table S2
155 summarizes all currently available WBE applications on pharmaceuticals. In this section, we will focus on the
156 most prevalent applications.



157

158 **Fig. 2 Overview of all current WBE applications on pharmaceuticals**

159 3.1. Spatio-temporal analysis of pharmaceutical consumption

160 Population-normalized biomarker mass loads can be employed as a proxy for consumption of the parent
 161 compound. This normalization enables the comparison of consumption patterns across different locations and
 162 different time points. This proxy is more appropriate compared to per capita doses per day since less uncertainty
 163 is associated with the back-calculations (i.e. large uncertainties associated with excretion factors).

164 3.1.1. Spatial comparisons of pharmaceutical use

165 45 out of the 64 studies demonstrate the ability of WBE to investigate spatial differences in the consumption of
 166 pharmaceuticals (Ahmed et al., 2020; Australian Crime Intelligence Commission, 2020; Bade, Ghetia, White, &
 167 Gerber, 2020; Baker, Ocenaskova, Kviclova, & Kasprzyk-Hordern, 2012; Baz-Lomba et al., 2016; Bodik et al.,
 168 2016; Boogaerts, Degreef, Covaci, & van Nuijs, 2019; Boogaerts, Quireyns, Covaci, De Loof, & van Nuijs, 2021;
 169 Burgard, Fuller, Becker, Ferrell, & Dinglasan-Panlilio, 2013; Castrignano et al., 2020; Causanilles, Emke, & de
 170 Voogt, 2016; Causanilles et al., 2018, 2017; P. M. Choi et al., 2018; P. Choi et al., 2019; Croft, Huffines, Pathak,
 171 & Subedi, 2020; Duan, Meng, Wen, & Chen, 2013; Escolà Casas et al., 2021; Fáberová, Bodfk, Ivanová, Grabic,
 172 & Mackul'ak, 2017; Fallati et al., 2020; Gao et al., 2016; Gomez-Canela, Sala-Comorera, Pueyo, Barata, & Lacorte,
 173 2019; Gushgari, Driver, Steele, & Halden, 2018; Kim & Oh, 2020; Krizman, Senta, Ahel, & Terzic, 2016;

174 Mackulak et al., 2016, 2019; Mirzaei, Mesdaghinia, Hoseini, & Yunesian, 2019; Ort, Lawrence, Reungoat,
175 Eaglesham, et al., 2010; Ostman, Fick, Nasstrom, & Lindberg, 2014; Pereira et al., 2015; Riva, Castiglioni,
176 Pacciani, & Zuccato, 2020; Shao et al., 2021; Skees, Foppe, Loganathan, & Subedi, 2018; Subedi, Balakrishna,
177 Joshua, & Kannan, 2017; Subedi & Kannan, 2015; Thiebault, Fougere, Destandau, Rety, & Jacob, 2017;
178 Thomaidis et al., 2016; Venhuis, de Voogt, Emke, Causanilles, & Keizers, 2014; Xiao et al., 2019; J.-H. Yan et
179 al., 2019; Q. Yan et al., 2014; Yargeau, Taylor, Li, Rodayan, & Metcalfe, 2014; Zhang et al., 2019, 2018). 34
180 studies indicate that WBE is sensitive enough to detect spatial variations in pharmaceutical use within countries
181 (town/village level) and, therefore, able to identify locations that differ in pharmaceutical use. While some
182 traditional DUR information sources may lack geospatial granularity, WBE can monitor consumption patterns at the
183 scale of suburbs and regions within a metropolitan area. In contrast to the studies that focus on differences in
184 pharmaceutical use within a specific country, only 8 studies provide a between-country spatial comparison (Baz-
185 Lomba et al., 2016; Castrignano et al., 2020; Causanilles et al., 2018; Duan et al., 2013; Fallati et al., 2020; Gao
186 et al., 2016; Subedi et al., 2017; Q. Yan et al., 2014). With traditional DUR information sources, it can be difficult
187 to compare pharmaceutical consumption between jurisdictions when organization of the health care systems and
188 therefore also data collection are completely different. In this light, Fallati et al. investigated the consumption of a
189 broad range of pharmaceuticals in different therapeutic classes with WBE in Malé compared to Milan and Oslo
190 (Fallati et al., 2020). Consumption in Malé could therefore be estimated through WBE as local prescription data
191 were not available.

192 An under-explored area is the use of WBE within sub-catchments such as hospitals or university campuses,
193 suburbs, or aged care facilities. Limited studies show the potential for WBE to monitor the consumption of
194 pharmaceuticals in subsets of the population and during specific events (Burgard et al., 2019; Gomez-Canela et
195 al., 2019; Gul, Gul, Stamper, Godfrey, & ElSohly, 2018; Gul, Stamper, Godfrey, Gul, & ElSohly, 2016; Gushgari
196 et al., 2018; Kosma, Nannou, Boti, & Albanis, 2019; Mackulak et al., 2016; Ort, Lawrence, Reungoat, Eaglesham,
197 et al., 2010; Stamper, Gul, Godfrey, Gul, & ElSohly, 2016; van Dyken et al., 2016). In this light, three WBE
198 studies focused on the consumption of opioids and benzodiazepines during football games at the Mississippi
199 University campus (Gul et al., 2018, 2016; Stamper et al., 2016) and found substantial increases in tramadol and
200 hydrocodone while concentrations in the municipal IWW samples were unchanged.

201 *3.1.2. Temporal analysis of pharmaceutical consumption*

202 Due to its high temporal resolution, WBE can be employed to obtain useful information on the consumption
203 patterns of pharmaceuticals over time. For instance, long-term trends can indicate whether pharmaceutical use is

204 stable, fluctuating, declining or on the rise. Additionally, seasonal patterns can highlight temporal changes with a
205 fixed frequency (e.g. between months of the year, between same months in different years). Furthermore, within-
206 week trends can reveal recreational pharmaceutical use versus habitual consumption (Tscharke, Chen, Gerber, &
207 White, 2016).

208 *3.1.2.1 Within-week trends in pharmaceutical loads*

209 To date, because sampling and analysis costs are typically relatively low, most studies have conducted 24-hour
210 composite sampling for multiple days. This allows for a temporal resolution that is difficult to obtain using other
211 methods. Differences in the mass loads measured on a daily basis can point to the recreational use of
212 pharmaceuticals on, for example, weekends as many pharmaceuticals, such as antihypertensives and
213 antidepressants, have low interdaily variability (Ahmed et al., 2020; Australian Crime Intelligence Commission,
214 2020; Been et al., 2015; Causanilles et al., 2016; Mastroianni, Lopez-Garcia, Postigo, Barcelo, & Lopez de Alda,
215 2017; Tscharke, Chen, Gerber, & White, 2015). Studies have thus found weekend differences in per capita
216 normalized mass loads for i) tramadol, methadone and possibly amitriptyline in the Czech Republic (Baker et al.,
217 2012), ii) tramadol, codeine and oxazepam in Slovakia (Mackulak et al., 2016) and iii) tramadol, diclofenac
218 (NSAID), methadone and antibiotics (sulfamethoxazole and trimethoprim) in France (Thiebault et al., 2017). Due
219 to the high frequency, analyses can also identify correlations between trends in the consumption of pharmaceuticals
220 that may be of concern.

221 Interestingly, two out of four studies estimating population-normalized mass loads of sildenafil found no difference
222 between weekend and weekday in the Netherlands and in 8 European cities (Causanilles et al., 2016, 2018), whereas
223 two studies, in England and in the Czech Republic, that document such a difference (Baker, Barron, & Kasprzyk-
224 Hordern, 2014; Baker et al., 2012). Similarly, the ADHD medication methylphenidate, having possible stimulant
225 effects, showed increased use on weekends in some European cities (Baz-Lomba et al., 2016) while this effect was
226 not found on a university campus (Gushgari et al., 2018).

227 *3.1.2.2 Seasonality and long-term temporal trends*

228 Most of the studies included in this review focused on a period of 7 days or less and fewer than 10 pharmaceuticals
229 for only one or two WWTPs, as indicated in Table S2. About half of the publications that assessed pharmaceutical
230 population-normalised mass loads in wastewater sampled more than 7 days and reported long-term temporal data
231 (i.e. trends that occur over several months or years). The most investigated substances were opioids, antibiotics,
232 benzodiazepines and antidepressants. In contrast to illicit drugs, short-term variations in pharmaceutical

233 consumption are less expected since pharmaceutical treatment requires frequent dose intervals and fixed treatment
234 schemes. For this reason, it is more interesting to monitor long-term consumption patterns in the use of
235 pharmaceuticals.

236 Higher mass loads were found in the winter for antidepressants, antibiotics (Golovko, Kumar, Fedorova, Randak,
237 & Grabic, 2014), tramadol and venlafaxine (Mackulak et al., 2016) while summer and autumn recorded higher
238 mass loads of NSAIDs (Papageorgiou, Kosma, & Lambropoulou, 2016), antihistamines, lipid regulators (Golovko
239 et al., 2014), codeine and oxazepam (Mackulak et al., 2016). For carbamazepine, oxazepam, methadone,
240 citalopram, metformine and memantine, population-normalized mass loads were relatively consistent between
241 seasons (Golovko et al., 2014; Mackulak et al., 2016; Xiao et al., 2019).

242 Pereira et al and Krizman et al (Krizman et al., 2016; Pereira et al., 2015) also highlighted that seasonal differences
243 in consumption estimates may be due to tourism, as higher use of some pharmaceuticals was observed during
244 summer periods at coastal tourist destinations, when compared with equivalent non-tourist destinations (Pereira et
245 al., 2015). This seasonal effect was addressed in Phung et al. by directly investigating the link between temperature
246 and consumption of a handful of pharmaceuticals (Phung et al., 2017). They found increased temperature
247 associated with increased naproxen (NSAID) loads, while decreased temperature related to increasing atenolol
248 consumption. No significant changes with temperature were observed for caffeine, codeine, carbamazepine and
249 hydrochlorothiazide. The changes in consumption measured in that study could also be due to changing population
250 demographics throughout the year, e.g. an efflux of older people during summer, making it more difficult to
251 compare studies with multiple years of data from multiple locations. However, these studies may highlight
252 seasonal effects on consumption of substances; changes that may be geographically or culturally specific.

253 Of the few long term studies available on pharmaceutical consumption key findings include a decreasing trends in
254 methadone consumption and an increase in oxycodone and fentanyl in Adelaide between 2011 and 2015 (Tscharke
255 et al., 2016). Sildenafil and metformin use increased in the Netherlands (Causanilles et al., 2016) and China (Xiao
256 et al., 2019) respectively over more than 3 years. Notably, consistent use patterns of methadone, morphine and
257 codeine were observed over time in Lausanne, Zagreb and Adelaide, respectively (Been et al., 2015; Krizman-
258 Matasic, Senta, Kostanjevecki, Ahel, & Terzic, 2019; Tscharke et al., 2016).

259 3.2. WBE biomarkers for disease and disease outbreaks

260 The WBE approach demonstrates that urinary human biomarkers identified and quantified in wastewater can
261 provide a perspective on a population's health in (near)-real time (Daughton, 2018). Specific pharmaceuticals or

262 a combination of pharmaceuticals are generally prescribed to treat diseases (Thomas & Reid, 2011). Several WBE
263 studies demonstrate the potential for WBE biomarkers to serve as a proxy measure for treated disease prevalence.
264 By measuring at high spatio-temporal resolution, it will be possible to monitor the evolution of different diseases
265 in specific locations and make area-specific assessments about their burden and monitor in near-real-time the
266 evolution of specific diseases.

267 This can however be complicated by a number of factors such as underdiagnosis or undertreatment. Additionally,
268 some diseases need a combination treatment while some pharmaceuticals are used to treat multiple diseases.
269 Uncertainties as arise for some diseases (e.g. depressive disorders), where non-pharmacological treatment might
270 be prioritized over pharmaceutical treatment. Furthermore a lack of compliance or recreational use should also be
271 taken into account. Therefore, it is imperative to proceed with caution when using WBE as a proxy for specific
272 disease prevalence.

273 To date, four Chinese WBE studies have used metformin as a proxy for type 2 diabetes (Shao et al., 2021; Song
274 et al., 2020; Xiao et al., 2019; J.-H. Yan et al., 2019). While they successfully captured metformin consumption in
275 Chinese communities, measurement of other antidiabetic drugs (e.g. sulfonylureas) would be necessary for a more
276 comprehensive picture on the prevalence of this disease. Insulin has been a key component of management in
277 patients with type 2 diabetes mellitus (T2DM), who require insulin therapy to maintain normal hemoglobin A1c
278 (HbA1c) levels (Scheurer, Brauch, & Lange, 2009). While most diabetic drugs are excreted in sufficient amounts
279 in urine (Gong, Goswami, Giacomini, Altman, & Klein, 2012; SHELDON, ANDERSON, & STONER, 1965),
280 almost all insulin is reabsorbed in the kidney with only trace amounts found in urine (Hanefeld, 2014). Therefore,
281 the use of WBE as a proxy for type 2 diabetes is not viable in the absence of suitable biomarkers for insulin and
282 additional biomarkers for antidiabetic drugs.

283 Ahmed et al. measured oxypurinol as a disease biomarker in wastewater to estimate the prevalence of treated gout
284 in Australia (Ahmed et al., 2020). Gout prevalence was estimated to be 2.7% in this study, which was comparable
285 to estimates from other epidemiologic studies (Proudman et al., 2019; Robinson, Kempe, Tebbutt, & Roberts,
286 2017). However, while defined daily doses (DDD) provided a good basis for comparing the consumption of
287 pharmaceuticals between different countries, it might be more challenging to use it to estimate the prevalence of
288 disease because of variations in doses prescribed per patient. Additionally, compliance is also universally low in
289 these patient groups which increases the uncertainty in these estimates (Silva et al., 2010).

290 Antibiotics have significantly reduced morbidity and mortality from many infectious diseases (Bérdy, 2012). Their
291 total global consumption increased 65% while consumption per capita increased 39% between 2000-2015 (Klein
292 et al., 2018). The excess or inappropriate use of antibiotics can lead to antibiotic resistance, as indicated by studies
293 showing an association between high use of antibiotics and enhanced antimicrobial resistance (AMR) (Chambers,
294 2001; Llor & Bjerrum, 2014). Wastewater has been used to monitor antibiotic presence and consumption patterns.
295 Zhang et al. measured loads of 23 antibiotics in wastewater from eight major WWTPs of Beijing (Zhang et al.,
296 2018). In another WBE study, antibiotic consumption was correlated with the flu season and the housing price
297 and population density of the catchment (Zhang et al., 2019). Another study in China assessed the use of six
298 antibiotics using WBE because there were no other data (Yuan, Liu, Huang, Yin, & Dang, 2016). In Milan, Italy,
299 antibiotic excretion was higher in winter than in summer, reflecting the higher rate of infections during winter
300 (Castiglioni et al., 2006). As antibiotic resistance genes emerge and spread globally, wastewater can monitor
301 sources of environmental antibiotic resistance. WBE can provide rapid information on community antibiotics
302 consumption in different time frames. A recent WBE study showed the power of analysing the consumption of
303 quinolones antibiotics and quinolones resistance genes in European wastewater. It found that higher daily load
304 qnrS gene were associated higher quinolone loads (Castrignano et al., 2020).

305 3.3. Relationship between socio-demographic catchment parameters and pharmaceutical use

306 The WBE approach allows the study of the relationships between consumption of chemicals and sociodemographic
307 features of catchment areas. This may extend the relevance of WBE in the social sciences to such fields as town
308 planning or local policy evaluation. These studies find predicted relationships between socioeconomic factors and
309 the consumption of legal and illegal compounds but they also uncovered novel relationships.

310 Changes in the socioeconomic composition of a population over time can be measured using WBE. In a 2016
311 Study, Thomaidis *et al.* analysed a suite of pharmaceuticals and drugs in the wastewater from Athens (Greece)
312 between 2010 and 2014, a period in which there was a severe economic downturn and the implementation of
313 austerity measures (Thomaidis et al., 2016). It showed staggering increases in the per capita consumption of
314 narcotic drugs such as methadone (7-fold) and psychiatric pharmaceuticals (35-fold), and antidepressants (11-
315 fold). By contrast, the consumption of amphetamine, antibiotics and NSAIDs decreased. This study demonstrates
316 how WBE can be used to document changes in drug consumption produced by large-scale socioeconomic
317 disruptions. Recently, Reinstadler et al. also showed the potential to investigate temporal changes during the
318 coronavirus disease 2019 (COVID-19) lockdown and quarantine in the catchment area of Innsbruck (Reinstadler
319 et al., 2021). This study showed that consumption of medicines prescribed for chronic pharmaceutical treatment

320 (e.g. oxazepam, carbamazepine, venlafaxine, etc.) remained unaffected by the public health crisis. Contrastingly,
321 the consumption of pharmaceuticals for short-term use (e.g. acetaminophen, codeine and trimethoprim) declined
322 during the COVID-19 pandemic, potentially as a result of improved population health or a reduction in the number
323 of consultations of medical doctors or pharmacies.

324 Housing prices and density have been shown to be associated with the consumption of pharmaceuticals. A 2018
325 study measured 37 pharmaceuticals from eight WWTPs in Beijing (China), and related these to the average
326 housing price and population density for each WWTP catchment (Zhang et al., 2018). These measures were highly
327 correlated ($r = 0.92 - 0.93$) with the total load of pharmaceuticals. Because of the sampling strategy in this study
328 (where one wastewater sample was deemed representative of a WWTP), these results may reflect increased
329 pharmaceutical consumption by transient residents (i.e. commuting workers) rather than residents. Nevertheless,
330 the results imply that higher economic status in China is linked to higher pharmaceutical use.

331 Relationships between WBE biomarkers and socioeconomic measures also include measures of demographics,
332 education and more. An Australian study measured a suite of mostly drug and pharmaceutical biomarkers from
333 wastewater samples collected at the same time as a national Census in 2019 (P. Choi et al., 2019). Per capita loads
334 of opioids, antipsychotics and antidepressants were significantly higher in catchments with older, lower
335 socioeconomic status populations. The loads of antibiotics cephalexin, sulfamethoxazole, and trimethoprim were
336 not associated with either age or socioeconomic status of the catchments. Strong correlations were found between
337 specific drugs and socioeconomic measures. There were for example correlations between: tramadol use and the
338 percentage of labourers in a population ($r = 0.84$), amitriptyline and a lack of high school education ($r = 0.77$), and
339 there was an inverse relationship between pregabalin and high income ($r = -0.77$) in Australia (P. Choi et al., 2019).
340 However, these associations may be influenced by the way reimbursement systems are set up. While WBE studies
341 examining socioeconomic status are unable to distinguish between correlation and causation, they can uncover
342 important insights into how drug and other chemical consumption patterns are associated with socioeconomic
343 characteristics.

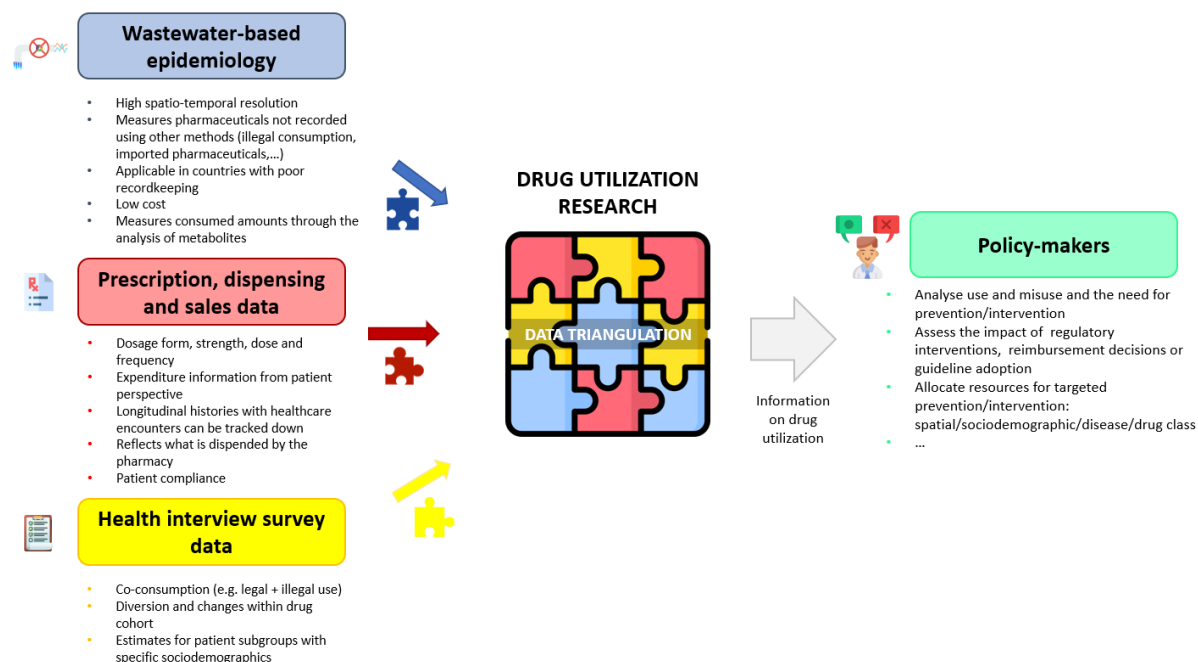
344 A WBE study in Milan (Italy) found a significant correlation between airborne particulate matter and salbutamol
345 (Fattore et al., 2016). This study clearly demonstrated the association between environmental changes (i.e. air
346 pollution, pollen season) and higher consumption of a pharmaceutical to treat respiratory disease. This study
347 demonstrates the potential of applying WBE to investigate environmental diseases. It provides a direct comparison

348 between pharmaceutical consumption and pollution levels at the same day, which can be used to investigate the
349 relationship between environmental exposure and disease.

350 4. Future perspectives and developments

351 4.1. WBE as a promising complementary information source for DUR

352 The current review demonstrates ways in which WBE can potentially be utilised as a complementary tool in DUR
353 but additional research is needed on methodological issues (i.e. in-sewer stability, pharmacokinetics, etc.) and data
354 triangulation. Nonetheless we observe an increasing number of WBE applications on pharmaceuticals. Fig. 3
355 indicates where WBE could be applied as a complementary strategy to aid in filling the current knowledge gaps
356 in the field of DUR and address the strengths of the different data sources. By triangulating data from the different
357 pharmacoepidemiologic information sources, it may be possible to estimate the prevalence of use of
358 pharmaceuticals more accurately. This information can be employed by policy-makers in the design and evaluation
359 of pharmaceutical regulations.



360

361 *Fig. 3 The place of WBE in the myriad of pharmacoepidemiological information sources in the context of drug utilization*
362 *research*

363 A major advantage of WBE is that it may provide estimates of consumption for pharmaceuticals which are not
364 recorded using other methods; either because they are consumed illegally, or that they are not recorded in existing
365 data sets (e.g. the Pharmaceutical Benefit Scheme in Australia does not include private scripts or in-hospital use;
366 some pharmaceuticals can be purchased without scripts) (Mellish et al., 2015). WBE can provide complementary

367 information on what proportion of pharmaceuticals that are sold, dispensed and/or prescribed are consumed by the
368 population because it measures consumption through human metabolic excretion products in wastewater.
369 Discrepancies between WBE and prescription data could indicate the degree of compliance to a medication
370 regimen at a population scale. A pharmaceutical prescribed to a patient is not necessarily taken by the patient in
371 prescribed amounts or the dispensed amounts (e.g. if some of the medicines are diverted to others).

372 Additionally, WBE may be a good alternative when prescription data are very difficult and sales data are too
373 expensive. For countries with limited prescription and or sales data, WBE could provide cost effective
374 measurements of the amounts of key compounds that are consumed. Additionally, many low income countries do
375 not have a prescription system and allow many pharmaceuticals to be sold over the counter with poor record
376 keeping (Borges, Chama, & Nilsson, 2016). WBE may be useful for surveillance of pharmaceutical regulation that
377 are not captured through traditional datasets (e.g. for pharmaceuticals not subsidized or off-label indications not
378 refunded by disability insurance). Some pharmaceuticals can also be obtained without prescription so their use
379 will not be included in prescription data (e.g. online internet trades, import from neighbouring countries, over-the-
380 counter sales, etc.).

381 The WBE approach can be especially helpful in monitoring the use of antibiotics (Zhang et al., 2019, 2018) and
382 misuse of potentially addictive pharmaceuticals, such as opioids and benzodiazepines (Bade et al., 2020; Centazzo,
383 Frederick, Jacox, Cheng, & Concheiro-Guisan, 2019; Croft et al., 2020; Duvallet, Hayes, Erickson, Chai, & Matus,
384 2020; Endo et al., 2020; Gushgari, Venkatesan, Chen, Steele, & Halden, 2019; Kim & Oh, 2020). Antibiotics are
385 supplied in several countries without a prescription (e.g. previously prescribed courses, local markets or stores,
386 diversion from families or friends) which facilitates the development and spread of antibiotic resistance (Bahta et
387 al., 2020; Berendonk et al., 2015; Llor & Cots, 2009). A recent study by Castrignanò et al. found that higher total
388 quinolone loads corresponded with a higher prevalence of quinolone resistance genes (measured through in-sewer
389 investigation of *qnrS* genes) in the catchment areas (Castrignano et al., 2020). If estimated antibiotic DDDs in
390 wastewater are substantially higher or lower than prescribed DDDs, the community may not be compliant with
391 therapy. It might be difficult to accurately estimate compliance to antibiotic treatment at a population scale due to
392 lack of knowledge of the optimal treatment length and varied treatment regimens for different infections.
393 Nonetheless, it is worth investigating trends in the discrepancies between prescribed amounts of antibiotics and
394 measured amounts in wastewater. Knowledge of total antibiotic loads is helpful to policy makers because of the
395 strong quantitative link between antibiotic use and antibiotic resistance (World Health Organization (WHO),
396 2018). Another critical component of this aspect is that WBE can capture uses of pharmaceuticals in animal

397 husbandry if the runoff from such facilities is connected to the WWTP. This is obviously of high relevance for
398 identifying inappropriate use of antibiotics leading to antimicrobial resistance as this is a global challenge with
399 particularly poor data on antibiotic use in the general community (World Health Organization (WHO), 2015).
400 Additionally, many non-antibiotic pharmaceuticals have shown ability to induce for antibiotic resistance
401 (Berendonk et al., 2015; Singh et al., 2019).

402 4.2. Agreement between WBE data and other DUR information sources

403 Some efforts have already been done to triangulate WBE data with other DUR information sources. These WBE
404 studies show reasonable relationships between WBE data on pharmaceuticals (e.g. oxazepam, atenolol, etc.) and
405 prescription and sales data (Baker et al., 2014; Baz-Lomba et al., 2016; Been et al., 2015; Escolà Casas et al., 2021;
406 He et al., 2020; Kasprzyk-Hordern et al., 2009; Rice, Kannan, Castrignanò, Jagadeesan, & Kasprzyk-Hordern,
407 2020; Riva et al., 2020; van Nuijs et al., 2015). For some pharmaceuticals (e.g. paracetamol, etc.), discrepancies
408 were reported which may reflect over-the-counter pharmaceutical sales that are not included in prescription data
409 (Baker et al., 2014; Crowley, White, Tschärke, & Gerber, 2017; van Nuijs et al., 2015). They could also reflect
410 illegal sales of pharmaceuticals and import/export/diversion of pharmaceuticals to other geographical areas.
411 Additionally, these differences may also arise from methodological uncertainties associated with WBE such as the
412 direct disposal of parent compounds in the sewer, poor accuracy of excretion rates used in WBE's back-
413 calculations and the complete/incomplete deconjugation of metabolites in the sewer (Escolà Casas et al., 2021).
414 As indicated by van Nuijs et al, predicted loads and measured loads from the analysis of biomarkers in IWW could
415 potentially not match accurately because WWTP catchment areas and postal codes do not correspond and not all
416 households may be connected to the sewer system (van Nuijs et al., 2015). Prescribed pharmaceuticals may not be
417 consumed by patients and the locality between the location of consumption and excretion might be different due
418 to commuting.

419 Riva et al. used WBE with four prescription medicines intended for chronic use, including citalopram, enalapril,
420 losartan and ramipril (Riva et al., 2020) in an attempt to assess compliance at a population level. WBE estimates
421 and prescription data showed good agreement for citalopram, enalapril and their metabolites but in other cases
422 there was a poor match. Although these discrepancies could be related to poor compliance or overuse, the authors
423 acknowledged that the disagreement may also be the result of methodological uncertainties associated with each
424 data source. In back-calculating daily defined doses they had to use potentially inaccurate excretion factors found
425 in pharmacokinetic and metabolism studies. These correction factors are often obtained from clinical trials
426 performed within a small subset of patients which may not be representative for the catchment population.

427 Additionally prescriptions may be incomplete in some areas (e.g. combination formulations only included in
428 national figures but not in the regional database) and local prescription data may not match completely with the
429 catchment area. Therefore, uncertainties in extrapolating to actual consumption should be addressed for each
430 individual compound.

431 4.3. Early-warning system for pharmaceutical misuse

432 The illegal use of pharmaceuticals cannot be monitored using conventional datasets. Data triangulation can
433 highlight potential discrepancies in the amounts used (e.g. identifying potential shifts to illicit use of
434 pharmaceuticals) and potentially estimate the number of users, at a local and national level. In order to enable this
435 comparison, it will be necessary to first monitor fluctuations in population-normalised mass loads of
436 pharmaceuticals to understand trends in consumption patterns at a population level. The high temporal resolution
437 of WBE enables researchers to monitor the evolution of the illicit market continuously, and with short-time lag.
438 This may enable policy-makers to counter more swiftly the spread of counterfeit medicines and the recreational
439 use of pharmaceuticals. It should be noted that while WBE can provide valuable information on the extent of
440 counterfeit medication it cannot provide data on the composition (i.e. impurities, lack of API, dose of API, etc.) of
441 counterfeit pharmaceuticals. WBE is not limited to measuring specific APIs; it can also be used to monitor their
442 by-products or precursors in communities. In addition, the effects of legal import and export of pharmaceuticals
443 (i.e. cheaper prices across national borders) cannot be excluded. These complications highlight the need for data
444 triangulation to obtain a comprehensive view of total consumption and to identifying the extent in which
445 pharmaceuticals are used appropriately.

446 In this light, Venhuis et al. highlighted the sale of sildenafil by online pharmacies in three Dutch communities
447 (Venhuis et al., 2014). They compared estimates of sildenafil use based on WBE data with dispensing data on
448 sildenafil that was legitimately sold. At least 60% of wastewater loads could not be explained by legal use of the
449 drug. Causanilles et al. found also big discrepancies between WBE data and prescription data, if these were
450 available (Causanilles et al., 2018) further documenting the power of WBE for documenting differences in local
451 consumption patterns. However, a major limitation of this study is that prescription data was estimated by
452 extrapolating the Dutch trend in prescription patterns, which might not be representative for other European
453 countries.

454 Furthermore, historical WBE data could be used to quickly identify new consumption patterns at high spatio-
455 temporal resolution early enough to avert an escalation in the use of pharmaceuticals. This approach can also be

456 used in specific locations to describe dissemination of a pattern of drug use of public health concern (e.g. increasing
457 opioid consumption in rural areas in Australia).

458 4.4. Monitoring the effect of interventions and quality-control system in decision-making processes

459 In contrast to illicit drugs, tobacco and alcohol (Australian Crime Intelligence Commission, 2020; Mackie et al.,
460 2019), WBE applications on pharmaceuticals have played a limited role in government strategies and decision-
461 making. We propose several ways in which WBE may provide a complementary monitoring approach for
462 governments and pharmaceutical policy makers.

463 The WBE approach provides a tool that can i) measure consumption of pharmaceuticals; ii) determine
464 consumption patterns of pharmaceuticals at different spatial (e.g. local, regional, national, international) and
465 temporal resolutions (e.g. daily, weekly, seasonally, yearly, etc.); and iii) by triangulating with other datasets,
466 assess the impact that strategies or interventions have on consumption. These uses are not limited to a specific
467 pharmaceutical, but could apply to a group of pharmaceuticals.

468 In this light, WBE may be particularly useful in monitoring the effect of an intervention or for assessing weekly
469 or seasonal trends in pharmaceutical consumption. This could include an intervention such as a rescheduling or
470 restricting of sale of a drug, a change in prescribing practice or regulations, or an education/advertising program
471 to change the behaviours of prescribers or individuals consuming pharmaceuticals. As yet, fewer studies have done
472 so reported this, however one notable example is Zhang et al, which evaluated a potential decline in antibiotic use
473 following interventions to prevent their prophylactic use during flu season in China (Zhang et al., 2019). One
474 limitation of their study was the absence of samples from the period before the change occurred, which necessitated
475 the use of other data sources. Partnerships between researchers and government agencies may assist in undertaking
476 evaluations of policy changes before, during and after they occur. Additionally, WBE studies of pharmaceuticals
477 are not necessarily limited in their choice of pharmaceuticals, as may be the case for surveys of drug use. If
478 researchers/policy advisors are interested in the effects of an intervention directed at one pharmaceutical, WBE
479 may be used to assess how this intervention has influenced consumption of another pharmaceutical. WBE could
480 quickly measure changes in the consumption of pharmaceuticals during public health crises. In this light, WBE
481 can be employed to investigate the impact of large-scale lifestyle disruptions such as the COVID-19 pandemic,
482 continuously and with a shorter time lag than prescription or sales data (Been et al., 2021; Reinstadler et al., 2021).

483 Additionally, WBE can provide location specific information for DUR, which could be used to set area-based
484 health care priorities for policy-makers. Areas with a higher burden of pharmaceutical misuse may require more

485 policy attention e.g. public or prescriber education, or the prevention of opioid overdose deaths by distributing
486 naloxone sprays (Endo et al., 2020). WBE can identify areas with a higher burden of both legal and illegal opioid
487 use. By prioritising problematic areas, decision-makers can respond to an evolving public health problems and
488 address the social determinants of a public health crisis. The EMCDDA has already shown the effectiveness of
489 this approach in addressing the consumption of illegal drugs in different European communities (European
490 Monitoring Centre for Drugs and Drug Addiction, 2019a).

491 In the same manner, WBE is also able to evaluate the effects of the promotional activities of pharmaceutical
492 companies, government or other institutions. This would enable policy-makers to assess if these approaches are
493 an efficient use of resources. If the measures don't produce the desired effect, policy makers might look for
494 different policies. WBE could be used, for example, to assess if statin compliance was adversely affected by
495 exaggerated media reports about side effects (Nordestgaard, 2018).

496 Besides that, WBE can be used to quickly evaluate the effect of policy changes and to optimize prevention and
497 harm reduction strategies targeting pharmaceuticals. Furthermore, by triangulating WBE data with other DUR data
498 from different locations and information sources, decision-makers can identify and promote best practice. In this
499 light, WBE can also be used to monitor and evaluate measures to ameliorate undesirable pharmaceutical use (e.g.
500 over-use of antibiotics, benzodiazepines, Z-drugs, opioids etc.). This is especially helpful in situations where
501 information on the consumption of pharmaceuticals needs to be obtained rapidly (e.g. socio-economic disruptions,
502 health crises, epidemics, etc.). These interventions do not always have to be restricted to governments. Other
503 organisations could potentially use WBE to assess the effects of their activities on the burden of pharmaceutical
504 use (e.g. non-profit organisations that intervene to diminish addiction).

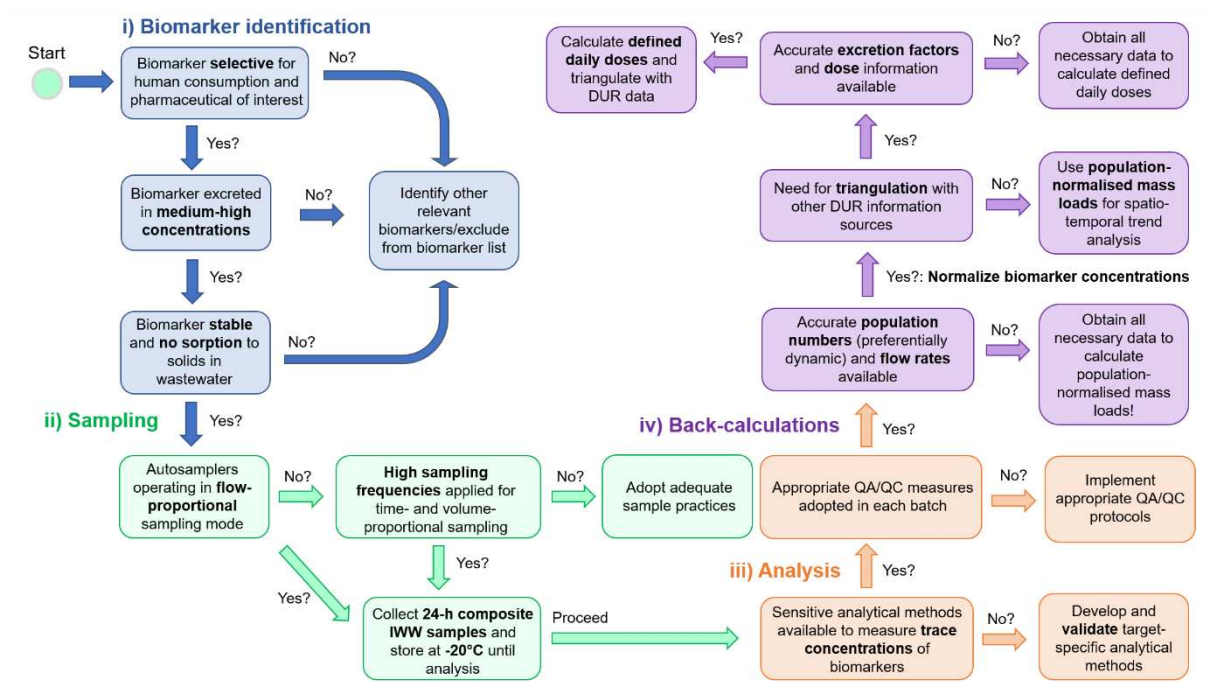
505 Furthermore, WBE can also provide an indicator of the extent of stockpiling of pharmaceuticals that have been
506 removed from the market. WBE can complement DUR data source because sales and prescriptions of these
507 pharmaceuticals are no longer available upon their removal from the market. It could also measure the extent of
508 stockpiling after the sale and distribution of scheduled pharmaceuticals is prohibited. If these pharmaceuticals are
509 still used in different communities, it would mean that they are acquired from other sources (e.g. online pharmacies,
510 imported from other countries). WBE can also be applied to investigate if pharmaceutical reformulations (e.g.
511 oxycodone reformulation in Australia to prevent injecting drug use) reduce consumption.

512 Two examples of governments that have used WBE for drug utilization research are the Australian National
513 Wastewater Drug Monitoring Program (NWDMP) and the New Zealand National Wastewater Testing Programs.

514 These campaigns monitor an array of both illicit and licit drug metabolites (e.g. fentanyl and oxycodone) in a large
 515 proportion of the population. The Australian NWDMP demonstrated large spatial differences in per capita
 516 consumption of some pharmaceuticals such as fentanyl and oxycodone and that regional consumption for these
 517 was higher than in the capital cities, as well as changes in consumption over time (Australian Crime Intelligence
 518 Commision, 2020).

519 5. Methodological limitations

520 Despite the progress made through more than a decade of research, WBE has some intrinsic uncertainties related
 521 to sampling, biomarker stability, chemical analysis and real-time population that remain to be addressed
 522 (Castiglioni et al., 2013). Fig. 4 focuses on the different steps of WBE that should be checked when adopting this
 523 methodology. This flowchart also indicates the several sources of uncertainty associated with the different steps
 524 that need to be resolved when applying the WBE approach.



525

526 **Fig. 4 Criteria for implementing the WBE approach**

527 Efforts have been spent to evaluate these uncertainties and improve the accuracy of WBE estimations. In this
 528 sense, continuous flow-proportional sampling of the influent is recommended best practice for sampling (Ort,
 529 Lawrence, Reungoat, & Mueller, 2010), but in reality different sampling methods including time proportional or
 530 volume proportional sampling are used for logistical reasons. Most of the reported studies use fixed population
 531 numbers and it is difficult to verify if the fluctuations in population-normalized mass loads were due to variations
 532 in population size or changes in consumption patterns. Therefore, it would be more appropriate to use dynamic

533 population size numbers using either an anthropogenic biomarker or other data such as mobile phone data (Been
534 et al., 2014; O'Brien et al., 2014; Thomas, Amador, Baz-Lomba, & Reid, 2017).

535 Metabolism and excretion of drugs are known to vary between individual or even within one individual under
536 different health condition. Therefore, the excretion factor (EF), derived from these processes, contributes notably
537 to the overall uncertainty of substance consumption estimation in WBE. EFs used in WBE applications are mostly
538 derived from pharmacokinetic studies that had a limited number of participants and so may not reflect the average
539 excretion profile in large populations (Kato, 1975; Klotz, 2011; Yasuda, Zhang, & Huang, 2008). Effort are being
540 made to refine the EF of different drugs (Gracia-Lor, Zuccato, & Castiglioni, 2016). In recent years, some EF
541 values derived from pharmacokinetics data were considered unsuitable for WBE application due to the large
542 uncertainty involved. Therefore, estimation of absolute figures on back-calculated doses should be addressed more
543 carefully. However, the primary focus of WBE has been to provide a complementary strategy to monitor spatial
544 and temporal trends in consumption patterns of pharmaceuticals. For this purpose, a viable approach to uncertainty
545 arising from EFs would be to use population-normalised mass loads and focus on the analysis of trends. Actually,
546 back-calculating defined daily doses should only be considered when triangulation with other relevant DUR
547 information sources is necessary. As an alternative, mass load of biomarkers in wastewater and prescription/sales
548 statistics have been used to refine the EF for WBE applications. In some cases they have shown that these EFs can
549 provide more accurate estimates of substance consumption in large populations (Thai, Lai, Bruno, et al., 2016).

550 Additional uncertainties can arise from the the non-use and/or direct disposal of unused drugs or the formation
551 from other chemicals or conjugated drugs (Bettington et al., 2018; Guirguis, 2010). This is especially an issue if
552 the parent drug is used as biomarker and if the unused drugs are disposed directly into the sewers (Petrie, Barden,
553 & Kasprzyk-Hordern, 2015). Most pharmaceuticals possess chirality and racemic analysis can be used to
554 distinguish between dumping and consumption of pharmaceuticals .

555 Stability of biomarkers is another source of uncertainties in WBE. Several studies have been carried out to
556 understand degradation/fate processes and evaluate and model the in-sample and in-sewer biomarker stability in
557 order to improve our understanding of the degree of this uncertainty (P. Choi et al., 2020; Gao et al., 2019; Li et
558 al., 2019; Ramin et al., 2017). Using preservatives such as HCl and storing the samples at low temperature
559 (preferably <-20 °C) are appropriate ways to minimise biomarker transformation. However, preservatives can only
560 be introduced at the point of collection and so do not account for any in-sewer degradation. For in-sewer stability,
561 the uncertainty could be much higher due to the lack of control over the microbiota present in the sewer system,

562 especially the sewer biofilms. Overall, higher biofilm area to bulk water volume ratio, higher wastewater
563 temperatures and longer hydraulic retention time promote biomarker transformation in the sewers (O'Brien et al.,
564 2017).

565 For some chemicals, sorption to particulate matter and/or biofilm can also contribute to the overall uncertainty of
566 the WBE approach, especially for biomarkers with high log K_{ow} values such as methadone, fluoxetine and
567 atorvastatin (Baker & Kasprzyk-Hordern, 2011c; Ramin et al., 2017).

568 **6. Conclusion**

569 Influent wastewater contains a wealth of information on population health and lifestyle and can be considered as
570 a mirror of the society. The growing number of applications demonstrates how WBE can reduce current knowledge
571 gaps in DUR. In the future, DUR could benefit from a better understanding of pharmaceutical use in the general
572 population. In this light, WBE could provide information on pharmaceutical use not recorded using other methods
573 (e.g. illegal use, imported pharmaceuticals,...) and could be employed as an alternative in countries with poor
574 recordkeeping. Additionally, WBE has the potential to be used as an indicator on health aspects of populations
575 which can be obtained with fast turn-around-times at high spatial and temporal resolutions and therefore to be used
576 as early-warning system for more detailed investigations. However, knowledge of methodological issues and
577 compound-specific uncertainties (i.e. biomarker excretion, in-sewer stability, population catchment size) will be
578 needed to convert concentrations of human biomarkers to population-normalised loads and/or pharmaceutical
579 consumption.

580 We also clearly emphasize the importance of triangulating multiple sources of information (e.g.
581 prescription/sales/dispensing data, health interview survey data,...) to validate WBE measurements and obtain a
582 multi-angled view on the use of pharmaceuticals in different locations. Additionally, the high spatio-temporal
583 frequency of WBE enables correlation analysis to investigate association between pharmaceutical consumption
584 and socio-demographics in specific communities. This adaptable sampling frequency also enables the investigation
585 of the impact of interventions (e.g. pharmaceutical rescheduling, restricted sales, education initiatives...) implemented by governmental agencies. It improves our understanding of pharmaceutical (mis)use for the
587 location-specific allocations of health care resources made by policy-makers. Finally, WBE is one of the few data
588 sources that can objectively measure the extent of illegal pharmaceutical consumption in the population. WBE and
589 other DUR information sources have their strength and weaknesses but the combination promises to be yield more
590 than the some of each.

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592 None to declare

593 **Declarations of conflicts of interest**

594 We hereby declare that there are no conflicts of interest. This is an original study and the work has not been
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603

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